Week 14 IP Part 3

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```
# Loading the arules library
suppressWarnings(
        suppressMessages(if
                         (!require(arules, quietly=TRUE))
                 install.packages("arules")))
library(arules)
```

```
#Load the data and preview the head
path="C:/Users/Rino/Desktop/Remote/Supermarket_Sales_Dataset II.csv"
super <-read.transactions(path, sep = ",")
```

```
## Warning in asMethod(object): removing duplicated items in transactions
```

```
# Verifying the object's class
class(super)
```

```
## [1] "transactions"
## attr(,"package")
## [1] "arules"
```

```
# Previewing our first 5 transactions
inspect(super[1:5])
```

```
##     items
## [1] {almonds,
##      antioxydant juice,
##      avocado,
##      cottage cheese,
##      energy drink,
##      frozen smoothie,
##      green grapes,
##      green tea,
##      honey,
##      low fat yogurt,
##      mineral water,
##      olive oil,
##      salad,
##      salmon,
##      shrimp,
```

```
##      spinach,
##      tomato juice,
##      vegetables mix,
##      whole weat flour,
##      yams}
## [2] {burgers,
##      eggs,
##      meatballs}
## [3] {chutney}
## [4] {avocado,
##      turkey}
## [5] {energy bar,
##      green tea,
##      milk,
##      mineral water,
##      whole wheat rice}
```

```
# ICreating a dataframe
items<-as.data.frame(itemLabels(super))
colnames(items) <- "Item"
head(items, 10)
```

```
##                Item
## 1            almonds
## 2  antioxydant juice
## 3          asparagus
## 4            avocado
## 5        babies food
## 6              bacon
## 7     barbecue sauce
## 8          black tea
## 9        blueberries
## 10        body spray
```

```
# Generating a summary of the transaction dataset
# ---
# This would give us some information such as the most purchased items,
# distribution of the item sets (no. of items purchased in each transaction), etc.
# ---
#
summary(super)
```

```
## transactions as itemMatrix in sparse format with
##  7501 rows (elements/itemsets/transactions) and
##  119 columns (items) and a density of 0.03288973
##
## most frequent items:
## mineral water          eggs     spaghetti  french fries     chocolate
##          1788          1348          1306          1282          1229
##       (Other)
##         22405
##
## element (itemset/transaction) length distribution:
```

```
## sizes
##    1    2    3    4    5    6    7    8    9   10   11   12   13   14   15   16
## 1754 1358 1044  816  667  493  391  324  259  139  102   67   40   22   17    4
##   18   19   20
##    1    2    1
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   2.000   3.000   3.914   5.000  20.000
##
## includes extended item information - examples:
##              labels
## 1           almonds
## 2 antioxydant juice
## 3         asparagus
```

There are 7501 transactions evident in our dataset.The most purchased items were mineral water, eggs, spaghetti, french fries and chocolate.

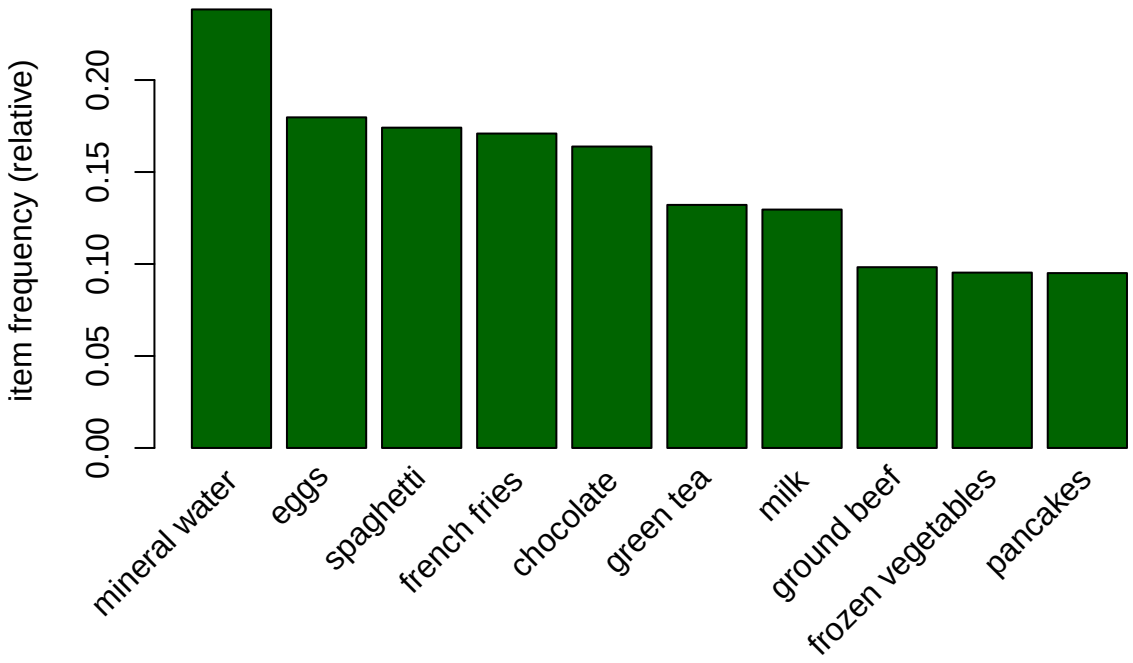
```
# Exploring the frequency of some articles and checking the transaction percentages of the first 20 ite
itemFrequency(super[, 1:20],type = "absolute")
```

```
##           almonds antioxydant juice         asparagus           avocado
##               153                67                36               250
##       babies food             bacon    barbecue sauce         black tea
##                34                65                81               107
##       blueberries        body spray           bramble          brownies
##                69                86                14               253
##         bug spray      burger sauce           burgers            butter
##                65                44               654               226
##              cake        candy bars           carrots       cauliflower
##               608                73               115                36
```

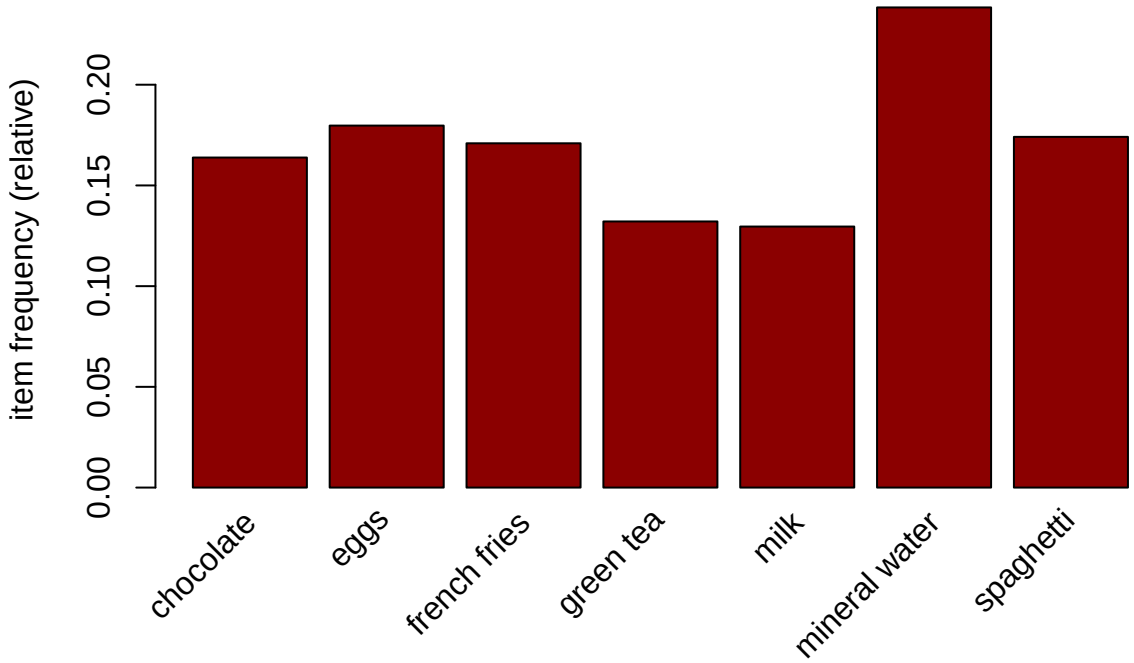
```
round(itemFrequency(super[, 1:20],type = "relative")*100,2)
```

```
##           almonds antioxydant juice         asparagus           avocado
##              2.04              0.89              0.48              3.33
##       babies food             bacon    barbecue sauce         black tea
##              0.45              0.87              1.08              1.43
##       blueberries        body spray           bramble          brownies
##              0.92              1.15              0.19              3.37
##         bug spray      burger sauce           burgers            butter
##              0.87              0.59              8.72              3.01
##              cake        candy bars           carrots       cauliflower
##              8.11              0.97              1.53              0.48
```

```
# plot the frequency of items
# Displaying top 10 most common items in the transactions dataset
itemFrequencyPlot(super, topN = 10,col="darkgreen")
```




```
# plot the frequency of items
# and the items whose relative importance is at least 10%
itemFrequencyPlot(super, support = 0.1,col="darkred")
```




```
# Building a model based on association rules using the apriori function
# We use Min Support as 0.001 and confidence as 0.8

rules <- apriori (super, parameter = list(supp = 0.001, conf = 0.8))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.8    0.1    1 none FALSE            TRUE       5   0.001      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 7
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[119 item(s), 7501 transaction(s)] done [0.00s].
## sorting and recoding items ... [116 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 6 done [0.00s].
## writing ... [74 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```
rules
```

```
## set of 74 rules
```

We have gotten 74 rules.

```
# However, in order to illustrate the sensitivity of the model to these two parameters, we will see wha

# Building a apriori model with Min Support as 0.002 and confidence as 0.8.
rules2 <- apriori (super,parameter = list(supp = 0.002, conf = 0.8))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.8    0.1    1 none FALSE            TRUE       5   0.002      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 15
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[119 item(s), 7501 transaction(s)] done [0.00s].
## sorting and recoding items ... [115 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 done [0.00s].
## writing ... [2 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```
rules2
```

```
## set of 2 rules
```

```
# Building apriori model with Min Support as 0.002 and confidence as 0.6.
rules3 <- apriori (super, parameter = list(supp = 0.001, conf = 0.6))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.6    0.1    1 none FALSE            TRUE       5   0.001      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
```

```
##
## Absolute minimum support count: 7
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[119 item(s), 7501 transaction(s)] done [0.00s].
## sorting and recoding items ... [116 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 6 done [0.01s].
## writing ... [545 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```
rules3
```

```
## set of 545 rules
```

In our first example, we increased the minimum support of 0.001 to 0.002 and model rules went from 74 to only 2. This would lead us to understand that using a high level of support can make the model lose interesting rules. In the second example, we decreased the minimum confidence level to 0.6 and the number of model rules went from 74 to 545 This would mean that using a low confidence level increases the number of rules to quite an extent and many will not be useful.

```
# Check the summaries of the rules
summary(rules)
```

```
## set of 74 rules
##
## rule length distribution (lhs + rhs):sizes
##  3  4  5  6
## 15 42 16  1
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   3.000   4.000   4.000   4.041   4.000   6.000
##
## summary of quality measures:
##     support           confidence        coverage             lift
##  Min.   :0.001067   Min.   :0.8000   Min.   :0.001067   Min.   : 3.356
##  1st Qu.:0.001067   1st Qu.:0.8000   1st Qu.:0.001333   1st Qu.: 3.432
##  Median :0.001133   Median :0.8333   Median :0.001333   Median : 3.795
##  Mean   :0.001256   Mean   :0.8504   Mean   :0.001479   Mean   : 4.823
##  3rd Qu.:0.001333   3rd Qu.:0.8889   3rd Qu.:0.001600   3rd Qu.: 4.877
##  Max.   :0.002533   Max.   :1.0000   Max.   :0.002666   Max.   :12.722
##      count
##  Min.   : 8.000
##  1st Qu.: 8.000
##  Median : 8.500
##  Mean   : 9.419
##  3rd Qu.:10.000
##  Max.   :19.000
##
## mining info:
##   data ntransactions support confidence
##  super          7501   0.001        0.8
```

```
# Observing rules built in our model i.e. first 5 model rules
inspect(rules[1:5])
```

```
##     lhs                              rhs             support     confidence
## [1] {frozen smoothie,spinach}    => {mineral water} 0.001066524 0.8888889
## [2] {bacon,pancakes}             => {spaghetti}     0.001733102 0.8125000
## [3] {nonfat milk,turkey}         => {mineral water} 0.001199840 0.8181818
## [4] {ground beef,nonfat milk}    => {mineral water} 0.001599787 0.8571429
## [5] {mushroom cream sauce,pasta} => {escalope}      0.002532996 0.9500000
##     coverage    lift      count
## [1] 0.001199840  3.729058  8
## [2] 0.002133049  4.666587 13
## [3] 0.001466471  3.432428  9
## [4] 0.001866418  3.595877 12
## [5] 0.002666311 11.976387 19
```

Interpretation: If a customer buys bacon and pancakes there is 81% of him or her purchasing spaghetti or if one buys mushrrom cream sauce and pasta there is 95% confidence of him or her to purchase escalope.

```
# Ordering these rules by a criteria such as the level of confidence
# then looking at the first five rules.
# We can also use different criteria such as: (by = "lift" or by = "support")
#
rules<-sort(rules, by="confidence", decreasing=TRUE)
inspect(rules[1:5])
```

```
##     lhs                                          rhs             support
## [1] {french fries,mushroom cream sauce,pasta} => {escalope}      0.001066524
## [2] {ground beef,light cream,olive oil}       => {mineral water} 0.001199840
## [3] {cake,meatballs,mineral water}            => {milk}          0.001066524
## [4] {cake,olive oil,shrimp}                   => {mineral water} 0.001199840
## [5] {mushroom cream sauce,pasta}              => {escalope}      0.002532996
##     confidence coverage    lift      count
## [1] 1.00       0.001066524 12.606723  8
## [2] 1.00       0.001199840  4.195190  9
## [3] 1.00       0.001066524  7.717078  8
## [4] 1.00       0.001199840  4.195190  9
## [5] 0.95       0.002666311 11.976387 19
```

#Promotion

```
# If we're interested in making a promotion relating to the sale of milk,
# we could create a subset of rules concerning these products

milk <- subset(rules, subset = rhs %pin% "milk")

# Then order by confidence
milk<-sort(milk, by="confidence", decreasing=TRUE)
inspect(milk[1:5])
```

```
##     lhs                                  rhs    support     confidence
```

```
## [1] {cake,meatballs,mineral water}    => {milk} 0.001066524 1.0000000
## [2] {escalope,hot dogs,mineral water} => {milk} 0.001066524 0.8888889
## [3] {meatballs,whole wheat pasta}     => {milk} 0.001333156 0.8333333
## [4] {black tea,frozen smoothie}       => {milk} 0.001199840 0.8181818
## [5] {burgers,ground beef,olive oil}   => {milk} 0.001066524 0.8000000
##     coverage    lift     count
## [1] 0.001066524 7.717078  8
## [2] 0.001199840 6.859625  8
## [3] 0.001599787 6.430898 10
## [4] 0.001466471 6.313973  9
## [5] 0.001333156 6.173663  8
```

```
# What if we wanted to determine items that customers might buy who have previously bought milk?
# Subset the rules
milk <- subset(rules, subset = lhs %pin% "milk")

# Order by confidence
milk<-sort(milk, by="confidence", decreasing=TRUE)

# inspect top 5
inspect(milk[1:5])
```

```
##     lhs                   rhs                    support confidence    coverage     lift count
## [1] {frozen vegetables,
##      milk,
##      spaghetti,
##      turkey}           => {mineral water}     0.001199840  0.9000000 0.001333156 3.775671     9
## [2] {cake,
##      meatballs,
##      milk}             => {mineral water}     0.001066524  0.8888889 0.001199840 3.729058     8
## [3] {burgers,
##      milk,
##      salmon}           => {spaghetti}         0.001066524  0.8888889 0.001199840 5.105326     8
## [4] {chocolate,
##      ground beef,
##      milk,
##      mineral water,
##      spaghetti}        => {frozen vegetables} 0.001066524  0.8888889 0.001199840 9.325253     8
## [5] {ground beef,
##      nonfat milk}      => {mineral water}     0.001599787  0.8571429 0.001866418 3.595877    12
```